

Object Detection in Dynamic Environmental Conditions using Evolutionary Multimodal Approach

Thesis by
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Dedication

I dedicate this thesis to my PhD supervisor Dr Zenon Chaczko for his support, guidance and a genuine reflection on my work. Without his encouragement and appropriate directions, this work would not have shaped up.

I also dedicate this thesis to my wife Manasi and my son Arnav for all along support during this long journey. Their sacrifices throughout these years allowed me to focus on this work.

Declaration of Authorship and Originality

I, Anup Vasant Kale, state that this thesis was authored by me, and that no material has been used in part or whole from other origins without full acknowledgement. All designs, results and theories of others that have been used in my thesis are referenced, and that assistance sources are recognised appropriately.

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Signature removed prior to publication.

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Abstract

Environmental dynamism and uncertainty can play a critical role in many problems involving camera-based detection of real-life objects. Uncertainty is witnessed due to the presence of climatic irregularities including illumination changes, smoke, heat-waves, dust and rain. In such scenarios, the visibility of an object can severely be influenced by both signal-noise and occlusion. With the recent developments in sensing technology and computing domains, it is still possible to overcome the shortcomings of uncertainty. Multimodal image processing techniques provide very encouraging results by reducing noise and improving visibility. However, the multimodality needs further improvements to enhance accuracy, performance and robustness. Here, an evolutionary multimodal method is proposed to succeed over the discussed limitations. An evolutionary biological inspiration is applied to create a set of computing models. The proposed set of innovative evolutionary algorithms allows to reduce redundancies in datasets and improve the detection process. Experimental validation is performed for testing proposed algorithms. A formal simulation method for data modelling process was incorporated in the testing scheme to emulate environmental variations. Rigorous experimenting and analysis show the merits of the proposed methodology. Notably, both the accuracy and performance can be improved significantly using the proposed evolutionary apparatus.

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Nomenclature

A

AI - Artificial intelligence is intelligence displayed by machines, in contrast with the natural intelligence displayed by animals.

ANN - Artificial Neural Network a concept inspired from biological neurons and used as a classification tool.

B

Bayesian Inference - A statistical inference which uses Bayes' Theorem to update the current probability for a hypothesis.

C

Classifier - A statistical classification algorithm in a software or computing engineering context used for analytical purposes.

D

DCA - Discriminant Classification Analysis is a type of classifier where groups of populations are known a priori and observations are classified into known populations.

Decision Trees - Decision Trees have a tree-like structure to model decisions and their possible consequences.

Deep Learning - A neural network variation which uses multiple layers of neurons to perform a heuristic analysis.

Dempster-Schafer - Dempster-Schafer approach is an evidence-based mathematical theory which is a generalization of Bayesian inference theory.

DWT - Discrete Wavelet Transform is a technique uses a set of small waves or wavelets to represent a signal.

E

EA - Evolutionary Algorithm is a subset of evolutionary computation, a generic population-based metaheuristic optimization algorithm.

EC - Evolutionary Computing or Computation is a family of algorithms for global optimization inspired by biological evolution.

ED - Environmental Dynamism is defined as any noticeable change in an environment due to natural or artificial causes.

G

GA - Genetic Algorithm is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms.

H

Heuristic - Heuristic is an approach to problem-solving that employs a practical method not guaranteed to be optimal, but sufficient for the immediate goals.

I

IEEE - The Institute of Electrical and Electronics Engineers is a non-profit professional association, fostering technical research and knowledge amongst academia and the engineering industry.

Inference - A conclusion calculated and thus determined based on the evidences collected from various cues.

K

KNN - K Nearest Neighbours is an algorithm very commonly used as a classification tool, a non-parametric method used for classification and regression.

L

LDA - Linear Discriminant Analysis is a statistical classification algorithm categorized under supervised machine learning.

Learning Classifier - A rule-based machine learning where the classifier learns from training datasets.

M

Multimodality - Multimodality provides multiple sources of data-channels for the same target for improved sensory perception.

N

Neural Network - A network of Biological neurons in the brain where every neuron represents an individual processing unit.

P

PCA - Principal Component Analysis is a computing procedure using orthogonal transformation to convert an observation set into a value set of linearly uncorrelated variables called principal components.

S

SVM - Support Vector Machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

